Competition Under Social Interactions and the Design of Education Policies

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Overview

Question: Model the education market in Peru

- What happens when students/families have preferences over their peers?

Approach: BLP with schools' shares of local education markets

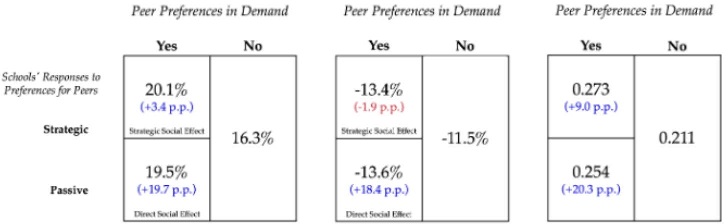
- Include (expected) peer quality in students' valuations of schools

Results: Firms have more market power but do not mark down quality by as much when accounting for social interactions

- The "best" policy from an equity/efficiency perspective is a combination of targeted vouchers and land lease subsidies

Motivation—Why include social interactions?

Figure 1: Decomposition of Schools' Incentives



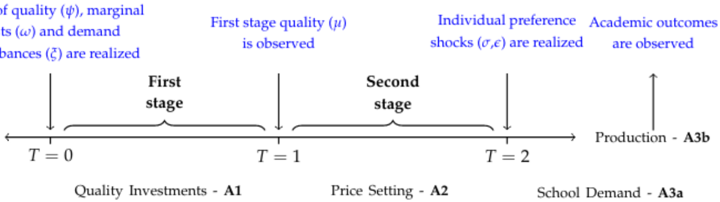
(a) Price Markup **(b)** Quality Markdown **(c)** Gap

Empirical Setting—First Graders in Peru

- Since 1998 there has been basically free entry (anyone can start a school)
- Teacher compensation reform in 2012
  - Use this to generate variation in wages across both time and locations
- School admissions reform in 2012
  - No more price discrimination
  - No more active selection/discrimination against students
- Teachers strike at Public Schools in 2017
  - Use this to generate an IV later in the paper

Model—Timing

Figure 2: Timing of the Model



1. Schools see their costs, choose a quality
2. Schools observe quality and choose prices to maximize profits
3. Individuals have preferences for schools; select the best school based on their expected peer quality
4. Students go to school, interact with each other, and have education outcomes

School Value-Added

$$Y_{ijt}(\tau) = \mathbf{X}'_{it}\pi^x + \theta_{jt}(\tau) + \epsilon_{ijt}$$

- $\theta_{ij}(\tau)$ is value-added; common for all students
  - τ only important for counterfactuals

- $x_i = (x_i^y, x_i^e)$ indicates high income/human capital

- $\mathbf{z}_{jt}$ includes the mean for x_i for school j at time t

Decomposing Value-Added

$$\theta_{jt}(\tau) = \mathbf{z}_{jt}(\tau)'\pi^z + \underbrace{\mathbf{I_{jt}}(\tau)'\pi^1(\tau) + \epsilon^s_{jt}(\tau)}_{\mu_{jt}(\tau)}$$

- $\mu_{ij}(\tau)$ is observable school quality
  - Does not try to break out the different components of μ; claims it is sufficient to have a measure of μ

- The peer-effects have three components:
  1. Direct effect of student characteristics on outcomes
  2. Direct effect of peer characteristics on outcomes
  3. Indirect effects of school composition on outcomes
     - For example, easier to hire good teachers if the school is full of well-behaved students

Demand for Schools

Schools have the following relevant characteristics:

- Quality: μ_{jt}
- Price: p_{jt}
- Student body characteristics: z^y_{jt}, z^e_{jt}
- Location: loc_j
- Private voucher network status: $net_{jt} = \mathbf{1}(j \in \Omega_{network})$
- Vector of other characteristics (religious status, etc.): r'_{jt}

Demand for Schools

$$U_{ijt} = \beta_i^{\mu}\mu_{jt} - \alpha_i p_{jt} + \beta_i^{z^y}\hat{z}_{jt}^{y} + \beta_i^{z^e}\hat{z}_{jt}^{e} + \beta_i^{d} D_{ij} + \beta_i^{net} net_{jt} + r'_{jt}\beta^r + \xi_{jt} + \epsilon_{ijt}$$

- Utility is over the *expectation* for student body composition
- Preference for quality and student body composition are heterogeneous along unobserved family characteristics

$$\alpha_i = \bar{\alpha} + \sum_{l=y,e} \alpha_l x_i^l, \quad \text{same for } \beta_i^d$$

$$\beta_i^{\mu} = \bar{\beta}^{\mu} + \textstyle\sum_{l=y,e} \beta_l^{\mu} x_i^l + \beta_u^{\mu} v_i, \quad \text{same for} \beta_i^{z^y} \text{ and } \beta_i^{z^e},$$

$$\mathsf{v}_i \sim \ln \mathcal{N}\left(m_v, \Sigma\right), \quad \beta_i^{\mathsf{net}} = \bar{\beta}^{\mathsf{net}} + \sigma^{\mathsf{net}} v_i^{\mathsf{net}}, \quad \text{with } v_i^{\mathsf{net}} \sim \mathcal{N}(0,1)$$

Beliefs about student body composition

- Families form beliefs that are consistent with the expectation of the realized student body composition of the school

- z^y and z^e satisfy the system of equations

$$\mathsf{Z}_{jt}^{x}\left(\mu, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e\right) = \frac{N \times \pi_{k=x}^{m} \times \sum_{n}^{N_m} \sum_{i}^{N_v} \mathcal{S}_{ijt}^{n,k=x}(\mu, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e) \times w^v \times w_{n,k=x}^{m}}{N \times \sum_{k}^{K} \sum_{n}^{N_m} \sum_{i}^{N_v} \mathcal{S}_{ijt}^{nk}(\mu, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e) \times w^v \times w_{nk}^{m} \times \pi_{k}^{m}}$$

For $x = \{y, e\}$ and $j = \left\{1, \ldots, N_j^m\right\}$

BLP share equations

- Assume ϵ_{ijt} has an EV distribution; the probability that a type-k family living at node n with unobservable type v_i selects school j is

$$\mathcal{S}_{ijt}^{nk}\left(\mu, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e\right) = \left(\frac{\exp\left(U_{ijt}\left(\mu, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e\right)\right)}{\sum_{l \in \Omega_{it}} \exp\left(U_{ilt}\left(\mu, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e\right)\right)} \right)$$

- We can aggregate across individuals to get market-level shares,

$$s_{jt}^{k}\left(\boldsymbol{\mu}, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e\right) = \sum_{n}^{N_m} s_{jt}^{nk} \cdot w_{nk}^{m}$$

$$s_{jt}\left(\boldsymbol{\mu}, \mathbf{p}, \mathbf{z}^y, \mathbf{z}^e\right) = \sum_{k}^{K} \sum_{n}^{N_m} s_{jt}^{nk} \cdot w_{nk}^{m} \cdot \pi_{k}^{m}$$

Supply—Costs

$$MC_j(\mu_{jt}) = \sum_l \gamma_l w_{jt}^l + \gamma_\mu \mu_{jt} + \omega_{jt}$$

$$FC_j(\mu_{jt}) = \sum_l \lambda_l w_{jt}^l + \psi_{jt}\mu_{jt''} \quad \text{where } \psi_{jt} = \bar{\psi}_j + \Delta\psi_{jt}$$

- ω_{jt} is the unobserved part of marginal cost
- ψ_{jt} is the fixed cost of providing quality μ_{jt}
  - Persistent component $\overline{psi}_j$ and shock $\Delta\psi_{jt}$

Second Stage—Pricing Decision

$$\pi_{jt}\left(\mu, \mathbf{p}, \mathbf{z}^{y}(\mathbf{p}), \mathbf{z}^{e}(\mathbf{p})\right) = \left(p_{jt} - MC_{jt}\left(\mu_{jt}\right)\right) \times N \times s_{jt}\left(\mu, \mathbf{p}, \mathbf{z}^{y}(\mathbf{p}), \mathbf{z}^{e}(\mathbf{p})\right)$$

$$p_{jt}^{*} = \underbrace{\sum_{l} \gamma_{l} w_{jt}^{l} + \gamma_{\mu}\mu_{jt} + \omega_{jt}}_{\text{Marginal Cost}} + \underbrace{s_{jt} \times \left(-\frac{ds_{jt}\left(\mu, \mathbf{p}, \mathbf{z}^{y}(\mathbf{p}), \mathbf{z}^{e}(\mathbf{p})\right)}{dp_{jt}}\right)^{-1}}_{\text{Price Markup with Social Interactions}}$$

- Pricing equation accounts for the effects social interactions have on the school's pricing strategy

- Considers both the direct and strategic effects of including $z^{y}(p)$ and $z^{e}(p)$ in demand

Incentives—Individual Demand

$$\frac{ds_{ijt}}{dp_{jt}} = \underbrace{\overbrace{\frac{\partial s_{ijt}\left(\boldsymbol{\mu}, \mathbf{p}, \mathbf{z}^y(\mathbf{p}), \mathbf{z}^e(\mathbf{p})\right)}{\partial p_{jt}}}^{\text{Sensitivity to price - (a)}}}_{\text{I - Direct Effect (Baseline + Social)}}$$

$$\underbrace{+ \sum_{l \in \Omega_{it}} \overbrace{\frac{\partial s_{ijt}\left(\boldsymbol{\mu}, \mathbf{p}, \mathbf{z}^y(\mathbf{p}), \mathbf{z}^e(\mathbf{p})\right)}{\partial z^y_{lt}}}^{\text{Sensitivity to peers (Poor) - (b)}} \times \overbrace{\frac{dz^y_{lt}\left(\boldsymbol{\mu}, \mathbf{p}, \mathbf{z}^y(\mathbf{p}), \mathbf{z}^e(\mathbf{p})\right)}{dp_{jt}}}^{\text{Change in peers (Poor) - (c)}} + \sum_{l \in \Omega_{it}} \overbrace{\frac{\partial s_{ijt}\left(\boldsymbol{\mu}, \mathbf{p}, \mathbf{z}^y(\mathbf{p}), \mathbf{z}^e(\mathbf{p})\right)}{\partial z^e_{lt}}}^{\text{Sensitivity to peers (M.Educ) - (d)}} \times \overbrace{\frac{dz^e_{lt}\left(\boldsymbol{\mu}, \mathbf{p}, \mathbf{z}^y(\mathbf{p}), \mathbf{z}^e(\mathbf{p})\right)}{dp_{jt}}}^{\text{Change in peers (M.Educ) - (e)}}}_{\text{II - Strategic Social Effect}}$$

Incentives—Individual Demand

- Term (I) is the direct effect of prices on demand

- Second term is the strategic social effect of prices on demand
  - (b) and (d) determine how sensitive demand is to peers
  - (c) and (e) determine how much peers respond to prices

- If prices and peers and strategic complements in demand, schools that are better at attracting high SES peers gain market power

First Stage—Quality

$$\pi_{jt}\left(\mu, \mathrm{p}^*(\mu), \mathbf{z}^y\left(\mu, \mathrm{p}^*(\mu)\right), \mathbf{z}^e\left(\mu, \mathrm{p}^*(\mu)\right)\right) =$$
$$\left(p_{jt} - MC_{jt}\left(\mu_{jt}\right)\right) \times N \times s_{jt}\left(\mu, \mathrm{p}^*(\mu), \mathbf{z}^y\left(\mu, \mathrm{p}^*(\mu)\right), \mathbf{z}^e\left(\mu, \mathrm{p}^*(\mu)\right)\right) - F_{jt}\left(\mu_j\right)$$

$$\frac{d\pi_{jt}}{d\mu_{jt}} = - \underbrace{\psi_{jt}}_{\Delta \text{ FC}} - \underbrace{\gamma_\mu \times N \times s_{jt}\left(\mu, \mathrm{p}^*(\mu), \mathbf{z}^y\left(\mu, \mathrm{p}^*(\mu)\right), \mathbf{z}^e\left(\mu, \mathbf{p}^*(\mu)\right)\right)}_{\text{Change in per student Margin} \times \text{N. of Students}}$$

$$+ \underbrace{\left(p^*_{jt}(\mu) - MC\left(\mu_{jt}\right)\right) \times N \times \frac{ds_{jt}\left(\mu, \mathbf{p}^*(\boldsymbol{\mu}), \mathbf{z}^y\left(\boldsymbol{\mu}, \mathbf{p}^*(\boldsymbol{\mu})\right), \mathbf{z}^e\left(\boldsymbol{\mu}, \mathbf{p}^*(\boldsymbol{\mu})\right)\right)}{d\mu_{jt}}}_{\text{Margin per student} \times \text{Change in N. of Students}}$$

Quality Markdown

$$\mu_{jt}^{*} = \frac{p - \sum_l \gamma_l w_{jt}^{l} - \omega_{jt}}{\gamma_\mu} - \frac{1}{\gamma_\mu} \times \frac{ds_{jt}(\mu, \cdot)^{-1}}{d\mu_{jt}} \times \left(\frac{\psi_{jt}}{N} + s_{jt}(\mu, \cdot) \times \gamma_\mu \right)$$

$$\text{Quality Markdown} = \mu_{jt}^{*} - \mu_{jt}^{\text{competitive}}$$

$$\mu_{jt}^{\text{competitive}} = \frac{p - \sum_l \gamma_l w_{jt}^{l} - \omega_{jt}}{\gamma_\mu + \frac{\psi_{jt}}{N \times s_{jt}(\mu, \cdot)}}$$

Quality Markdown

$$
\begin{aligned}
\frac{ds_{ijt}}{d\mu_{jt}} = & \underbrace{\overbrace{\frac{\partial s_{ijt}}{\partial \mu_{jt}}}^{\substack{\text{Sensitivity to}\\ \text{Quality - (f)}}}}_{\substack{\text{I - Direct Effect}\\ \text{(Baseline + Social)}}} + \underbrace{\sum_{l\neq j} \overbrace{\frac{\partial s_{ijt}}{\partial p_{lt}}}^{\substack{\text{Sensitivity to}\\ \text{Prices - (a)}}} \times \overbrace{\frac{\partial p^*_{lt}}{\partial \mu_{jt}}}^{\substack{\text{Direct Change}\\ \text{in Prices - (g)}}}}_{\text{II - Strategic Pricing Effect}} + \underbrace{\sum_{l\in\Omega_{it}} \overbrace{\frac{\partial s_{ijt}}{\partial z^y_{lt}}}^{\substack{\text{Sensitivity to}\\ \text{Peers (Poor) - (b)}}} \times \overbrace{\left(\frac{\partial z^y_{lt}}{\partial \mu_{jt}} + \sum_{r\in\Omega_{it}} \frac{dz^y_{lt}}{dp_{rt}} \times \frac{dp^*_{rt}}{d\mu_{jt}}\right)}^{\text{Change in peers (Poor)}}}_{\text{III - Strategic Social Effect (...)}} \\
& \underbrace{+ \sum_{l\in\Omega_{it}} \underbrace{\overbrace{\frac{\partial s_{ijt}}{\partial z^e_{lt}}}^{\substack{\text{Sensitivity to}\\ \text{Peers (Educ)}}}}_{\text{(d)}} \times \overbrace{\left(\underbrace{\frac{\partial z^e_{lt}}{\partial \mu_{jt}}}_{(j)} + \sum_{r\in\Omega_{it}} \underbrace{\frac{dz^e_{lt}}{dp_{rt}}}_{(e)} \times \underbrace{\frac{dp^*_{rt}}{d\mu_{jt}}}_{(i)}\right)}^{\text{Change in peers (Educ)}} + \sum_{l\neq j} \overbrace{\frac{\partial s_{ijt}}{\partial p_{lt}}}^{\substack{\text{Sensitivity to}\\ \text{Prices - (a)}}} \times \overbrace{\sum_{r\in\Omega_{it}} \left(\frac{\partial p^*_{lt}}{\partial z^y_{rt}} \times \frac{\partial z^y_{rt}}{\partial \mu_{jt}} + \frac{\partial p^*_{lt}}{\partial z^e_{rt}} \times \frac{\partial z^e_{rt}}{\partial \mu_{jt}}\right)}^{\substack{\text{Indirect Change}\\ \text{in Prices - (k)}}}}_{\text{(...) Strategic Social Effect}}
\end{aligned}
$$

Quality Markdown

- Quality and peers are direct substitutes in demand
- Firms that are better at attracting high SES peers have more market power
- Term (II) is a result of the two-stage nature of the game
- Term (III) has two interesting features:
  - Strategic social effect on quality reduces strategic incentives to exert market power and reduce quality
  - Accounts for the screening incentives in the second stage of the pricing game ($a \times k$)

Equilibrium

A rational-expectations equilibrium is a tuple

$$\{\{\mathbf{z}^y, \mathbf{z}^e\}\, j \in J, \{\mathbf{p}\} j \in J, \{\boldsymbol{u}\}, j \in J\}$$

that satisfies

1. $$\hat{\mathbf{z}}_i^y = \mathbf{z}^y \text{ and } \hat{\mathbf{z}}_i^e = \mathbf{z}^e, \forall i \in I$$

2. $$p_j^* \left(\mathbf{p}_{-j}^*\right) = \underset{p}{\operatorname{argmax}} \pi_j \left(\mu, p, \mathbf{p}_{-j}^*, \mathbf{z}^y \left(p, \mathbf{p}_{-j}^*\right), \mathbf{z}^e \left(p, \mathbf{p}_{-j}^*\right)\right), \forall j \in J$$

3. $$\mu_j^* \left(\boldsymbol{\mu}_{-j}^*\right) = \underset{\mu}{\operatorname{argmax}} \pi_j \left(\mu, \mu_{-j}^*, \mathbf{p}^* \left(\mu, \mu_{-j}^*\right), \mathbf{z}^y \left(\mathbf{p}^* \left(\mu, \mu_{-j}^*\right)\right), \mathbf{z}^e \left(\mathbf{p}^* \left(\mu, \mu_{-j}^*\right)\right)\right)$$

Assumptions

- Does not model education production function; instead infers MCs from markups and uses these estimated MCs in simulations
- Counterfactuals must take MC parameters as invariant; cannot address equilibrium effects (e.g. changes in wages)
- Parameters for student valuations are just weights they place on characteristics, not deep structural preferences

Data—Students and Families

1. Student education data (enrollment and performance)
2. Birth and health records
3. National Household Survey data
4. National Census
5. Scholarship application

Data—Schools

1. School Characteristics

2. Tuition

3. Teacher data

4. Survey data
   - Principals (2016)
   - Prices (2016)
   - More prices (2019)

Data—Market Level

1. National Census (SES characteristics for each market)

2. College graduates

Identification—BLP Instruments

1. Lagged strike exposure index (2 indexes, distance weighted)
2. Local market strucutre: share of private and number of schools (distance weighted)
3. Local demographics: share high SES (income and education, distance weighted)

Lagged strike exposure should only be coordinated with unions' political factors, which is plausibly excluded from parents' and schools' decisions, but schools with a higher predicted strike probability are more likely to lose students.

Instruments for price and quality

1. Public school teacher wage index (distance weighted)
2. Public school teacher vacancies for post-reform contracts (distance weighted)
3. Stock of graduates with education degrees ($t-1$, distance weighted)
4. Test scores for teachers ($t-1$, distance weighted)
5. Flow of new graduates with education degrees to the market

RD to identify price parameters

- RD around scholarship cutoff
- Scholarship applicants are probably a selected sample; implement sample correction
- Use distance to test location as an instrument for scholarship application

Estimating Value-Added

$$Y_{ijt} = X_{it}^{VA}\beta + \theta_{jt} + \epsilon_{ijt}$$

- Can estimate by FE or RE
- Not enough data to include lagged test scores
- Instead use very, very rich controls for academic results

Separating Observable Quality and Peer Effects

- Estimate $\hat{\theta}_{jt}$ in a first-stage

- Project $\hat{\theta}_j$ onto peers and inputs, plus a school fixed effect:

$$\hat{\theta}_{jt} = \mathbf{z}'_{jt}\pi^z_j + \mathbf{I'_{jt}}\pi^l + \alpha_j + \epsilon_{jt}$$

- Recover μ_{jt} by subtracting $z_{jt}(\tau)'\hat{\pi}^z_j$ from $\hat{\theta}_{jt}$

Estimation—Parameters

Three sets of parameters

1. $\theta_1 = \beta^r$, linear parameters in utility function
2. $\theta_2 = \tilde{\alpha}, \tilde{\beta}^q, \tilde{\beta}^z, \tilde{\beta}^d$, non-linear parameters in utility function
3. $\theta_3 = \gamma$, marginal cost parameter

Estimation—Moments

Aggregate moments for shares:

$$G^1(\theta_2) = s_{jt}^k - s_{jt}^k(\theta_2)$$

Micro Moments:

$$G_q^2(\theta_2) = \sum_{i \in N_{kt}^m} q_{ik} - \sum_{n}^{N_m} \sum_{j}^{N_{m,t}^f} s_{jt}^{nk}(\theta_2) \cdot w_{nk}^m \cdot q_{jn}$$

Selection Correction for Scholarship Application Moments:

$$G^3(\theta_2, \eta) = \frac{1}{N_s} \nabla_\eta \sum_i \log \ell_i(\theta_2, \eta)$$

Estimation—Moments

Regression Discontinuity Quasi-Experimental Moments:

$$\mathsf{G}^4(\theta_2) = \frac{1}{N_s}\sum_{s=1}^{N_s}\left(Z'\left(Y_l^{sim}(\theta_2) - X\hat{\beta}_l^{RD'}\right)\right)' WZ'\left(Y_l^{sim}(\theta_2) - X\hat{\beta}_l^{RD'}\right)$$

IV Moments:

$$G^5(\theta_2) = \begin{pmatrix} \xi_{jt} \\ \omega_{jt}^c \\ \Delta\psi_{jt} \end{pmatrix} \cdot IV'$$

Estimate parameters via GMM according to BLP

Results—Peer Effects

Table 4: IV Estimates for Peer Effects

	VA-I (Full Period)		VA-I (Full Period)		VA-I (2018 only)	
	Coef.	StdErr	Coef.	StdErr	Coef.	StdErr
Share of High SES (Income)	0.078	(0.030)	0.081	(0.032)	0.085	(0.038)
Share of High SES (Education)	0.107	(0.040)	0.117	(0.053)	0.112	(0.048)
Share of High SES (Income × Education)	0.023	(0.009)	0.029	(0.010)	0.031	(0.014)
Year FE	×					
School District FE	×		×		×	
R^2	0.137		0.923		0.735	
N obs	23,543		5,734		5,734	

Results—Demand Model

Table 6: Demand Model Estimates

Panel A: Linear parameters	Parameter	Coeff.	Std Err.
Quality	$\bar{\beta}^q$	0.734†	(0.341)
Price	$\bar{\beta}^p$	-2.397†	(1.114)
Peers (Income)	$\bar{\beta}^{zy}$	0.448†	(0.207)
Peers (Educ.)	$\bar{\beta}^{ze}$	0.603†	(0.274)
Distance	$\bar{\beta}^d$	-1.288†	(0.651)
Panel B: Observed Heterogeneity			
Quality			
Family Income	β^q_y	0.657†	(0.331)
Mothers' Educ	β^q_e	0.464†	(0.156)
Price			
Family Income	α_y	0.567†	(0.275)
Mothers' Educ	α_e	1.321†	(0.652)
Peers (Income)			
Family Income	β^{zy}_y	0.641†	(0.326)
Mothers' Educ	β^{zy}_e	0.706†	(0.275)
Peers (Educ.)			
Family Income	β^{ze}_y	0.389†	(0.176)
Mothers' Educ	β^{ze}_e	0.310†	(0.107)
Distance			
Family Income	β^d_y	0.234†	(0.109)
Mothers' Educ	β^d_e	0.554†	(0.282)

Results—Demand Model

Panel C: Unobserved Heterogeneity

Means			
Price	m_v^p	0.013†	(0.006)
Peers (Educ.)	m_v^{ze}	0.007†	(0.003)
Peers (Poor)	m_v^{zy}	0.019†	(0.009)
Variance - Covariance			
Price	σ_p	0.132†	(0.064)
Peers (Income)	σ_{zy}	0.179	(0.098)
Peers (Educ.)	σ_{ze}	0.211†	(0.101)
Peers (Corr.)	$\rho_{zy,ze}$	0.019	(0.010)
Scholarship Network	σ_s	0.399	(0.237)

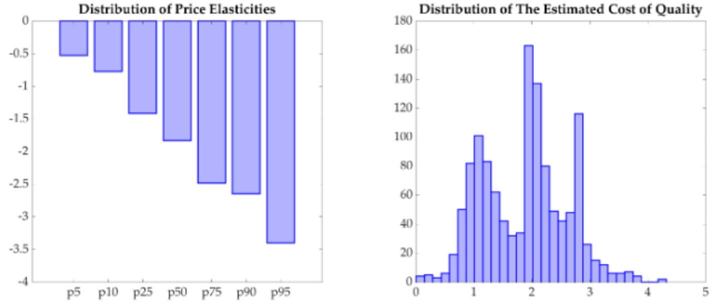
Panel D: Application Costs

Fixed - Constant	$\bar{\eta}$	2.424†	(0.064)
Fixed - Educ.	η_e	-1.345†	(0.101)
Distance - Constant	$\bar{\eta}^d$	1.9290	(0.010)
Distance - Educ.	η_e^d	-0.432	(0.098)

Notes: † indicates significance at 0.05 confidence level. The table presents results from the estimation using thirty-nine markets. Random coefficients have a lognormal distribution, and the simulation is done using the sparse grid rule of Heiss and Winschel (2008) for dimension 4 with the Gauss-Hermite rule.

Results—Elasticities and Costs of Quality

Figure 10: Model Results



(a) Price Elasticities

(b) Fixed Cost of Quality

Notes: This figure shows additional model results. Panel (a) shows the distribution of the price elasticities implied by the demand parameters. Panel (b) shows the distribution of the estimated fixed cost of increasing quality, $\bar{\psi}_j$, for private schools.

Results—Demand Model

- These results agree with the theoretical predictions of the model
- Peers and value-added are direct substitutes in demand
- Prices are direct complements in demand with peers
- Prices and peers are strategic complements in demand

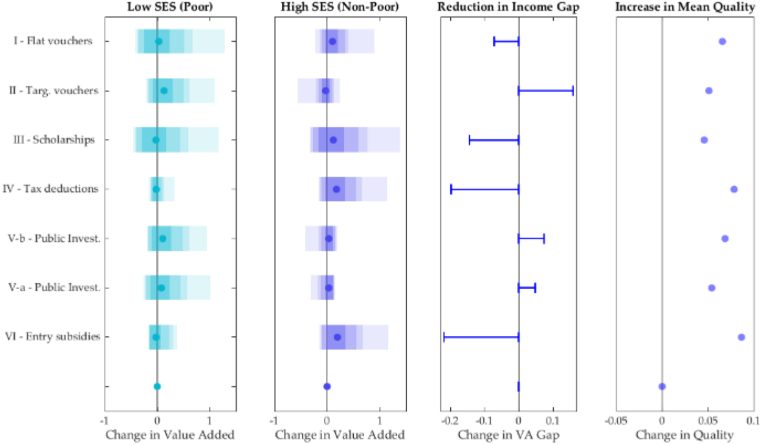
Counterfactuals

Table 1: Education Policies for Counterfactual Analysis

N	Policy	Mechanism	Counterfactual in the model	Examples
I	Universal Vouchers	Demand	Subsidies for all students $v_i = \bar{v}$	US[i], Denmark, NZ, Holland, Sweeden[ii]
II	Targeted Vouchers	Demand	Subsidies for poor students $v_i = \bar{v} \times \mathbb{1}[x_i^y = 0]$	Chile[iii], Colombia[iv], US[v]
III	Scholarships	Demand	Subsidies for skilled students $v_i = \bar{v} \times \mathbb{1}[x_i^e = 1]$	US, Peru (Private)[vi], UK (Public)[vii]
IV	Tuition tax deductions	Demand	Subsidies for non-poor students $v_i = \bar{v} \times \mathbb{1}[x_i^y = 1]$	US[viii], UK, Dominican Rep.
V	Public school investment	Supply	Change in market structure $\Omega'_{it} = \Omega_{it} \cup j', \mu_j > \bar{\mu}_j$	New York, Dominican Rep.[ix]
VI	Land lease subsidies	Supply	Entry incentives Δ in $F_{jt} \implies \Omega''_{it} = \Omega_{it} \cup j''$	India[x]

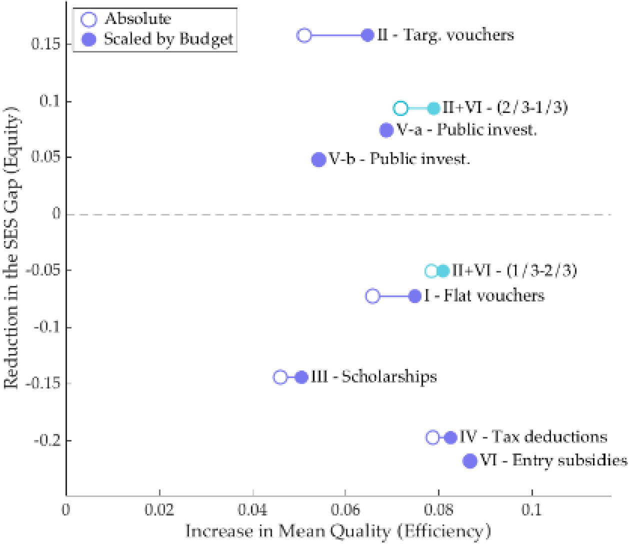
Counterfactuals

Figure 13: Counterfactuals



Counterfactuals

Figure 15: Equity-Efficiency Trade-off for Counterfactual Policies



Conclusion/Question

1. Do you buy the application of BLP to the student/school question?

2. Do you think that including peer effects in this model is a worthwhile contribution?
   - Do you think this is the right way to do it?

3. What are other things (in addition to or instead of peer effects) that might be interesting to add?